Analysis of Forest Cover Change Detection

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Abstract

While the concepts of change detection analysis is not new, the emergence of new imaging sensors and geospatial technologies has created a need for image processing techniques that can integrate observation from a variety of different sensors and datasets to map, detect and monitor forest resources. In addition to timber, forests provide such resources as grazing land for animals, wildlife habitat, water resources and recreation areas and these are threatened constantly by both human impacts like forest fires, air pollution, clearing for agricultural uses, and illegal cutting. Farming activities, continued sand winning operations and the allocation of plots of land to prospective developers in and around the catchments of the Owabi dam pose a serious threat to the forest covers and the lifespan of the dam. The overall objective of this study is to map out and analyze the structural changes of forest cover using Landsat and ASTER imageries of the study area. A supervised classification was performed on three multi-temporal satellite imageries and a total of eight major land use and land cover (LULC) classes were identified and mapped.

By using post-classification techniques, from 1986 to 2002 and 2002 to 2007 the forest cover has decreased by an amount of 2136.6 ha and 1231.56 ha respectively representing 24.7% and 14.2%. Generally, the results indicate that from 1986 to 2007, forest cover reduced by 3368.16 ha, representing 38.9%. Decrease in vegetation has been as a result of anthropogenic activities in the study area. An NDVI analysis was performed on these images and it was noted that there was no significant difference between the NDVI classification and the supervised classification of the images. Overlay of the reserved forest of the 1974 and the classified map of 2007 shows vegetation changed during 1986-2007 remarkably.

Keywords

Land Use; Land Cover; Forest Cover; Change Detection; Classification

Introduction

The use of remote sensing data in recent times has been of immense help in monitoring the changing pattern of forest cover. It provides some of the most accurate means of measuring the extent and pattern of changes in cover conditions over a period of time [25]. Satellite data have become a major application in forest change detection because of the repetitive coverage of the satellites at short intervals [24].Forest cover today is altered primarily by direct human use and any conception of global change must include the pervasive influence of human action on land surface conditions and processes [35]. As indicated in their studies general information about change is necessary for updating forest cover maps and the management of natural resources.

Change detection as defined by Singh [32] is a process of identifying changes in the state of an object or phenomenon by observing images at different times. According to the IGBP/IHDP [18], change detection studies seek to know (i) pattern of forest cover change, (ii) processes of forest cover change, and (iii) human response to forest cover change. Lambin and Strahler [22] also listed five categories of causes that influenced forest cover change. Boakye et al [7], explain that changes in forest cover are often the result of anthropogenic pressure (e.g. population growth) and natural factors such as variability in climate. They reported that tropical forests are exploited for varied purposes such as timber, slash-and-burn cultivation and pasture development. They further explained that degradation of forest have impact on catchment processes and biochemical cycles and leads to soil erosion and water shortage not only in the regions immediately affected by deforestation, but also in reasonably distant areas.

Forests have long been regarded as a national treasure in Ghana and in addition to timber; these forests provide such resources as grazing land for animals, wildlife habitat, water resources, tourism and outdoor recreation areas. They are also important for preserving biodiversity, as they provide a habitat for certain specialised forest-related species [28]. However, farming activities and continued sand winning operations in and around the catchments of the Owabi Dam (i.e., the study area), which provides potable

water to residents of Kumasi, are posing a serious threat to the lifespan of the dam. It has been detected that there was serious logging and clearing of the bushes in the catchments to the extent that many trees have all been cut down to pave way for sand winning operations. A lot of pillars had been erected giving an indication that someone was allocating the plots of land to prospective developers [16]. For instance a number of houses totalling about 400 are known to have been illegally constructed in the Owabi catchment area and out of this 140 of them were demolished in 1998 [16]. In order to formulate and exercise efficient forest management policies and practices, it is important to extract reliable the land use and cover (LULC) information [23].

Mapping LULC is now the standard way to monitor changes and in order to monitor land use change and development, a change detection analysis was performed to determine the nature; extent and rate of land cover change over time and space. The results will quantify the land cover change patterns in the area and demonstrate the potential of multi-temporal satellite data to map and analyse changes in land cover in spatio-temporal framework. This can be used as inputs to land management and policy decisions with regard to varied themes that have link with space such as urbanization, water management, deforestation and land degradation. The aim of this research is to analyse and monitor the spatio-temporal LULC change patterns using multi-temporal satellite images from the period 1986-2007 within the Owabi catchment. Concurrent with this aim is to identify and quantify the major LULC classes, to detect changes using change detection techniques, and to identify the key driver(s) of change within the study area.

Many studies [7, 29, 31] have been performed to identify factors that cause changes in forest cover in developing countries. One of those factors is inappropriate agricultural technology used in farm lands located around the forest area [3]. The misuse of forest resources due to the centralization of forest management policy is considered as another factor for deforestation [31]. Moreover, Boltzet al. [8] mentioned that conventional logging operation with unplanned-selective logging method also becomes one factor of deforestation. However, the most important factor that causes deforestation comes from illegal logging and trade [4, 36]. According to Ringrose et al [29] LULC change in Africa is currently accelerating and causing widespread environmental problems and thus needs to be mapped. This is important because the changing pattern of LULC reflect changing economic and social conditions. Monitoring such changes is important for coordinated actions at the national and international levels [5].

Miwei [26] monitored ephemeral vegetation in Poyang Lake using satellite imagery. The study monitored the change in area of ephemeral vegetation by analysing time series of satellite imagery and investigates how this change is related to changes in hydrological conditions. Ahmad [1], used remote sensing and GIS tools for mapping a dry shrub forest for biodiversity conservation planning by using salt range of Pakistan as a case study. Joshi [21] investigated spatial detection and prediction of Banmara invasion. In his assessment, he illustrated the potential threat of Banmara invasion into forest areas disturbed by anthropogenic activities. The study concluded that intensive forest use, human interference and environmental conditions have led to forest degradation resulting in an increased invasion of Banmara. Adia and Rabiu [2] investigated the spatio-temporal change detection of vegetation cover of Jos and its surrounding areas. The study used satellite images to generate change maps of the vegetation cover for the respective dates and find out the pattern of change. In the following Sections, the methodology used in this research is introduced. This focuses on mapping the extent and rate of forest change patterns. Also, it outlines the mode of data capture and processing to come out with the expected result. Section three contains the results obtained from the processed data and its analyses and Section four concludes the research and outlines some recommendations for future research.

Mapping the Extent and Rate of Forest Cover Change Patterns

This section describes the study area and the four phases of research methodology -pre-processing, post classification change analysis, comparative analysis and accuracy assessment. These phases were investigated in manually controlled environment, typically using RS and GIS tools.

Study Area

Owabi forest reserve (Figure 1b) is located between latitudes 6º 47' 42.7" and 6º 42' 6" North and longitudes 1º 43' 16.8" and 1º 35' 29.4" West of Kumasi in Ashanti region (Figure 1b) and is one of the smallest forest conservation areas in Ghana. The highest point is

about 259.56 meters above sea level. The study area is bounded by the districts of Atwima, Kwabre and Kumasi Metro. This area consists of a wildlife sanctuary which is the smallest of the four wildlife protected areas in Ghana. It is about 13km² in size, and lies approximately 23km northwest of Kumasi. It has an inner Sanctuary of about 7km, which surrounds a lake, formed by the damming of the Owabi river in 1928. The study area was designated on 22nd February 1988 with Ramsar site number 393 [14].The region is invariably rich with indigenous water birds including Ardeidae (herons, bitterns, etc.), and to various species of wintering and staging birds during migration. There are about 161 kinds of birds consisting of 29 families in this area. The sanctuary is also the only inland Ramsar site in Ghana.

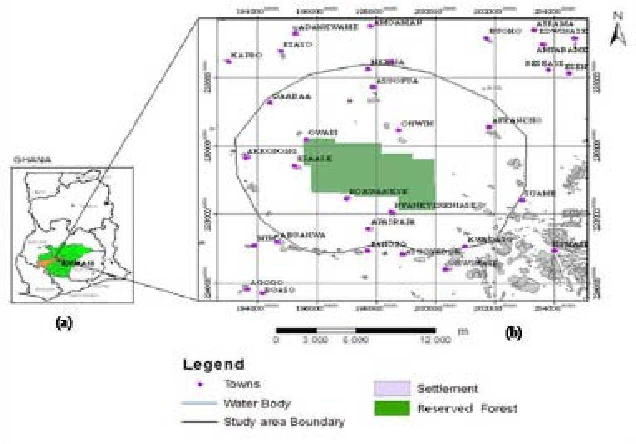

FIG. 1 LOCATION OF STUDY AREA IN GHANA

Data Set

In this study, multi-temporal satellite images used include Landsat TM (Figure 2a), ASTER (Figure 2b) and Landsat ETM (Figure 2c). Landsat TM and ETM were taken on 11th January 1986 and 24th February 2007 respectively and having row and path of 194 and 55. Both sensors have spatial resolution of 30. Radiometric corrections were applied to the images. In addition, the relatively new ASTER level 1B image with the acquisition date of 15th January 2002 was used. As stated in Forkuo [15] this image is geometrically and radiometrically calibrated with 15m spatial resolution in the visible and near-infrared. For effective integration, the ASTER image data was re-sampled to the same resolution of the Landsat imagery.

The acquisition dates of the ASTER image and the two Landsat images employed in this change detection process fall within the same season. In order to align the images to Ghana grid coordinates, geo-referencing was performed using Ground Control Points (GCPs). Some of the commonly used GCP features on the earth's surface in the images include: intersection of roads, natural utility infrastructure (e.g., fire hydrants, corner of building and manhole covers), survey benchmarks and intersection of agricultural plots of land [15]. Research has indicated that the number, precision and spatial distribution of GCPs affect the accuracy and the reliability of the geo-referenced image [15]. As can be seen in Figure 2d, these GCPs were evenly distributed with GPS survey and a total of 341 GCPs with overall root mean square error of ½ of a pixel were located both in the images covering the study area.

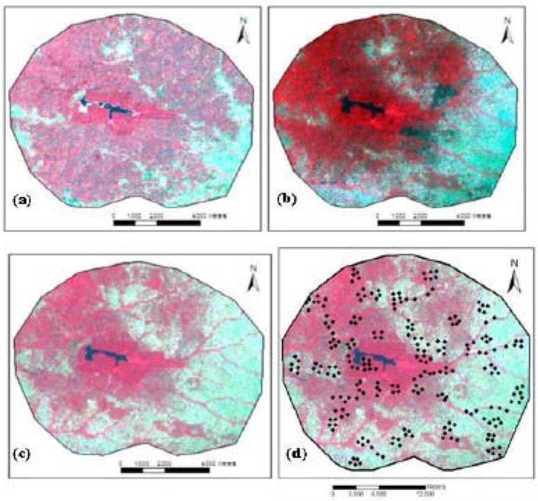

FIG. 2 SATELLITE IMAGES OF THE STUDY AREA (A, B, C) AND THE DISTRIBUTION OF GCPS (D)

Land Cover Land Use Classification

A supervised classification of the satellite imagery was used to produce LULC classes. Maximum likelihood classification technique was performed using all spectral bands in each satellite image. This is the most widely adopted classification algorithm [23]. The images of the study area were taken through three stages to generate land cover classes of the study area. These include: (1) feature extraction; (2) selection of training data (signatures); and (3) selection of suitable classification approaches. The following eight land cover and use classes were identified and mapped: water, bare soil, grassland, built-up, sparse forest, high density forest, croplands and wetlands. After the classification, 341 sample points were obtained from the field for accuracy assessment. These samples points were used for classification accuracy assessment (as discussed in Section III.B). The image classification was guided by reconnaissance information gathered from the field of the study area. The results are shown in Figures 3, 5 and 7 with eight classes for 1996, 2002 and

2007 satellite images respectively. The classified image was further reclassified as forest and non-forest area and stratified random sample points within the forest area were generated.

Post-Classification Comparison

Of many methods (i.e., Image overlay, change vector analysis, principal component analysis, image rationing) that are available for change detection in forest cover [13], post classification comparison was used in this research. In this technique, images of different dates are firstly classified and labelled individually. Using both supervised and unsupervised classification, the classified images were then compared and changed areas extracted [32].Since the errors in the individual classified images could be reflected in the final change image post-classification requires individual classified images to be as exact as possible [33]. Post-classification comparison has been used, e.g., to detect: non-urban to urban, or forest to cropland, conversion and changes in general land use, wetlands and forests.

Normalized Difference Vegetation Index (NDVI)

Several vegetation indices have been developed of which, NDVI is the most commonly used one despite the development of many new indices that take into account soil behaviour [6, 27]. It is used to distinguish healthy vegetation from others or from non-vegetated areas [23, 34] using red and near-infrared reflectance values and this was integrated in the post-classification analysis to discriminate between the green cover and barren land. Theoretically, NDVI threshold value ranges between -1 to +1. Measured value range from -0.35 (water) through zero (soil) to +0.6 (dense green vegetation). Based on grey scale this corresponds to a pixel digital number of 135 or higher. It can be concluded that the more positive the NDVI the more green vegetation there is within a pixel. Detailed information on NDVI can be found in [19].This research used NDVI based on the red band and near-infrared band of Landsat and ASTER imageries and this was derived using expression given in Equations 1 and 2 for ASTER for Landsat imageries respectively.

$$NDVI = \frac{NIR - R}{NIR + R} \tag{1}$$

$$NDVI = \frac{TM4 - TM3}{TM4 + TM3} \tag{2}$$

Where; NIR is the spectral reflectance measurements acquired in the near-infrared region (band), R is the spectral reflectance measurements acquired in the red region (band). In the case of Landsat image data TM4 is near infrared band, TM3 is red band. The 1986, 2002 and 2007 satellite images were reclassified based on the NDVI threshold values and the results are shown in Figure 9

Classification Accuracy Assessment using Error Matrix

In the study, the classification accuracy was assessed by an error matrix. This is a square array of numbers organized in rows and columns which expresses the number of sample units (i.e. pixels and clusters of pixels) assigned to a particular category relative to the actual category as indicated by reference data [9]. Many measurements have been proposed to improve the interpretation of the error matrix, among which the Kappa coefficient is one of the most popular measures. It is a discrete multivariate technique used in accuracy assessment [11]. The Kappa coefficient represents the proportion of agreement obtained after removing the proportion of agreement that could be expected to occur by chance [12]. Kappa coefficient is widely used because all elements in the classification error matrix, and not just the main diagonal, contribute to its calculation and because it compensates for change agreement [30].

The Kappa coefficient lies typically on a scale between 0 (no reduction in error) and 1 (complete reduction of error). The latter indicates complete agreement, and is often multiplied by 100 to give a percentage measure of classification accuracy. Kappa values are also characterized into 3 groupings: a value greater than 0.80 (80%) represents strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents moderate agreement, and a value below 0.40 (40%) represents poor agreement [10]. Kappa can be used as a measure of agreement between model predictions and reality [10] or to determine if the values contained in an error matrix represent a result significantly better than random [20]. Kappa according to Jensen and Cowen [20] was computed using Equation (3). The accuracy and kappa statistics are summarised in Table 1.

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \tag{3}$$

Where N is the total number of sites in the matrix, r is the number of rows in the matrix, xii is the number in

row i and column i, $x+i$ is the total for row i, and $xi+$ is the total for column. After the classification, 341 sample points were obtained from the field for accuracy assessment.

Results and Discussions

In this Section the results of the supervised LULC classifications using Landsat and ASTER images are presented and discussed. The classification accuracy and Kappa statistics are discussed. Also, the spatial extent of LULC after classification is discussed.

Analysis of LULC Area Change

The supervised classification of the images yielded three land cover maps of the study area (as shown in Figures 3, 5 and 7). As already mentioned the following eight (8) LULC classes were distinguished after classification; bare soil/sand, built-up, croplands, grassland, high density forest, sparse forest, water and wetlands.

1) LULC Map from 1986 Landsat TM Imagery:

The supervised classification of the 1986 landsat ETM image yielded the LULC classes shown in Figure 3. These classes were calculated (based on the count of pixels) in hectares (ha) and also in percentages (%).

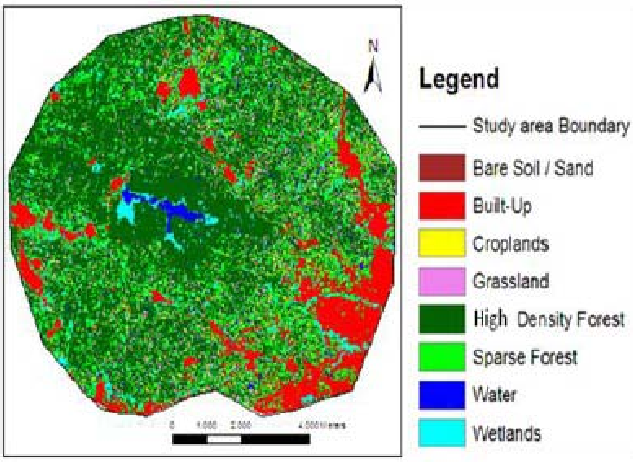

Fig. 3 1986 classified map of Owabi catchment

FIG. 3 1986 CLASSIFIED MAP OF OWABI CATCHMENT

As can be seen in Figures 4a and 4b the land area of high density forest cover is 4347.27 ha, representing 50.21% of the total area. This is basically found in the Northern, Eastern and Western part of the map with the highest concentration around the Owabi River. Similarly, sparse forest covers the land area 1843.74ha (representing 21.29%) which is scattered around the North, South, East and the Western parts of the area with very small patches within the forest reservoir.

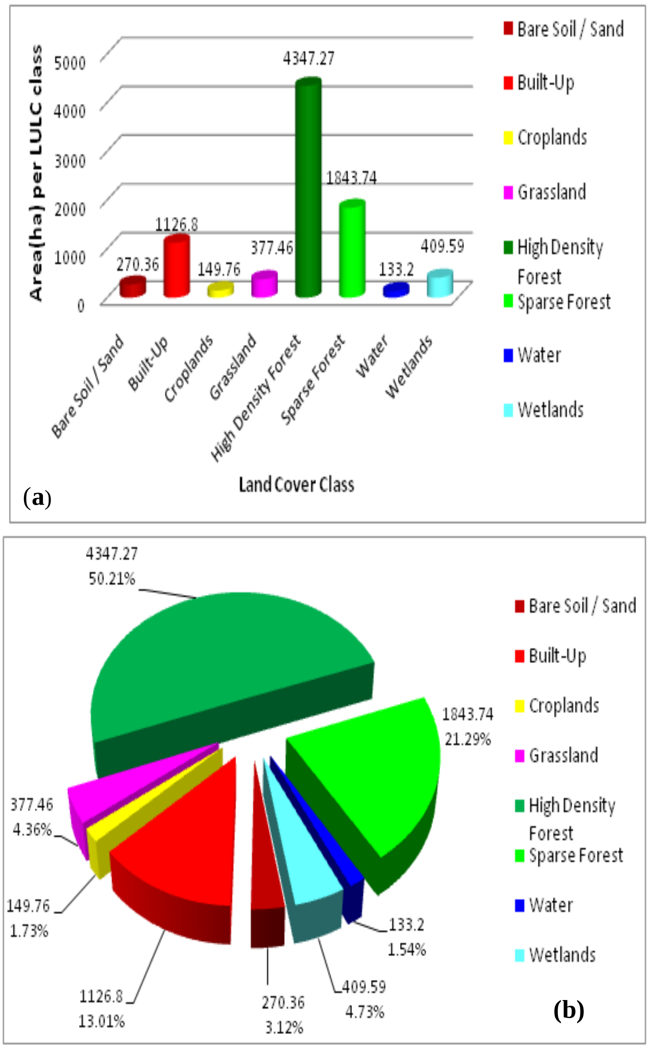

FIG. 4 LAND AREAS (HA) OF 1986 LULC CLASSES (A) AND THEIR PERCENTAGES (B)

Built-up covers land area of 1126.8ha (which represents 13.01%) and is located mainly around the North, South, East and Western part of the study area. Wetland area is 409.59 ha (i.e., 4.73%) and its area coverage consists of small patches along river courses and marshy areas. Grassland has an area of 377.46 ha (representing 4.36%) with small patches scattered across the entire map with the exception of the reservoir. The bare soil/sand and croplands have respective land areas of 270.36 ha (i.e., 3.12%) and 149.79 ha (i.e., 1.73%) with former scattered at the Northern, Southern Western parts respectively while the latter has very small patches scattered across the map except the reservoir. The land area of water 133.2 ha representing 1.54% is mainly concentrated within the reservoir with very small of it in other areas.

2) LULC Map from 2002 ASTER Image

The supervised classification procedures applied to the 2002 ASTER image yielded land cover map (as can be seen in Figure 5) with the High Density Forest

occupying the largest area coverage as compared to other LULC classes having 2389.32ha which represents 27.60% (Figures 6a and 6b).

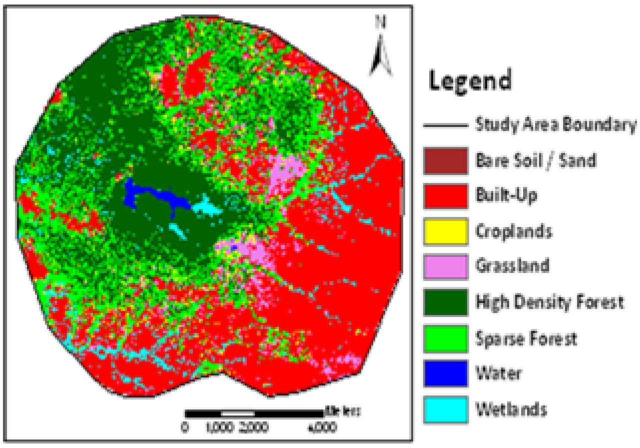

FIG. 5 2002 CLASSIFIED MAP OF OWABI CATCHMENT

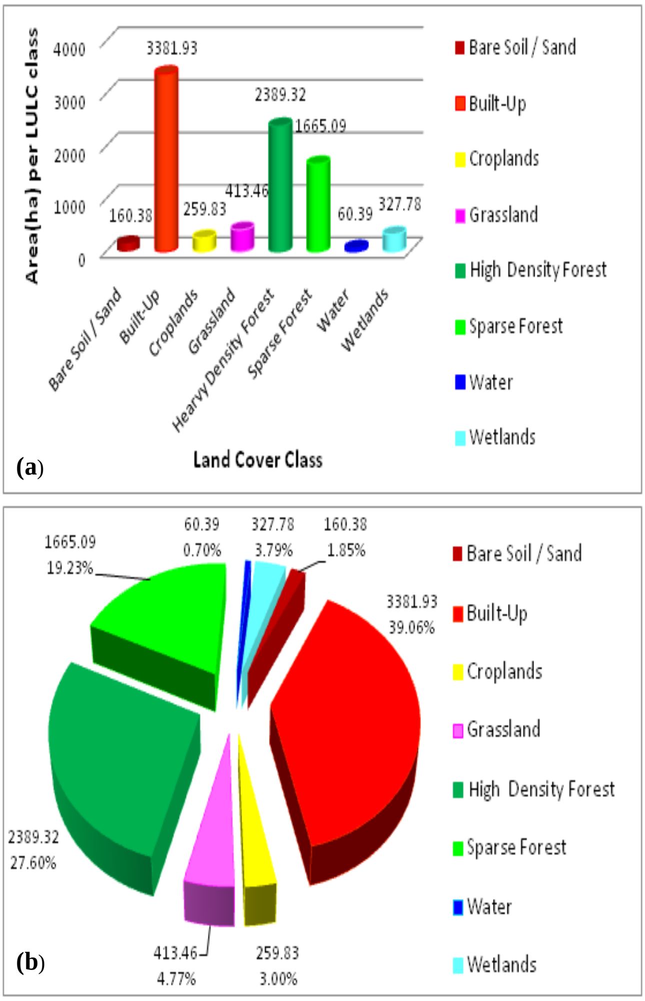

FIG. 6 LAND AREAS (HA) OF 2002 LULC CLASSES (A) AND THEIR PERCENTAGES (B)

This is concentrated around the Owabi river with a few around North Western part of the area. Sparse Forest covers an area of 1665.09ha (19.23%) and mainly around the Northern, Western, Southern, Eastern corners and also along the fringes of the reservoir. Wetlands could be mainly found along river courses and marshy areas with an area of 327.78 ha (3.79%). Grassland has an area of 413.46 ha (4.77%) which is centred at the Eastern and South Eastern portions of the map. Built-up occupies an area of 3381.93 ha (39.06%) and mainly concentrated at the Northern, Eastern, Southern and small patches around the western parts of the map. Croplands having an area of 259.83 ha (3.00%) are concentrated along the entire scene, mainly around the fringes of the reservoir. Bare Soil/Sand has an area of 160.38 ha (1.85%) with very small patches within the entire scene except the reservoir. Water having 60.39 ha (0.70%) is the least area coverage and mainly concentrated within the reservoir with very small of it in other areas

3) *Lulc Map from 2007 Landsat ETM Image*

The 2007 Landsat ETM after classification procedures yielded Land cover map displayed in Figure 7. It is evident from Figures 8a and 8b that the land area of High Density Forest in 2007 is 1363.95ha (15.75%) which is concentrated around the Owabi River with a few around North Western part of the area. Sparse Forest covers an area of 1458.9ha, (16.85%) and mainly around the North Western, Southern, small patches around the North and along the fringes of the reservoir. Built-up occupies the largest area coverage as compared to other LULC classes having 4351.95ha (50.26%). This is concentrated at the entire map mainly; Northern, Southern, Eastern and small patches around the western part of the map. Wetlands could be mainly found along river courses and marshy areas with an area of 288.63ha (3.33%).Grassland has an area of 300.87ha (3.48%) with very small patches centred around North, North East, South East, Western and on the fringes of the reservoir. Bare Soil/Sand has an area of 358.02ha (4.14%) with very small patches within the entire scene except the reservoir.

Croplands having an area of 451.26 ha (5.21%) is concentrated along the entire scene, mainly around the fringes of the reservoir, North Eastern, South Eastern and Western parts of the map. Water, having 84.6 ha (0.98%) is the least area coverage and mainly concentrated within the reservoir with very small of it in other areas. The LULC maps indicate that some changes of the landscape have occurred over a 21 year period from 1986 through 2002 to 2007.

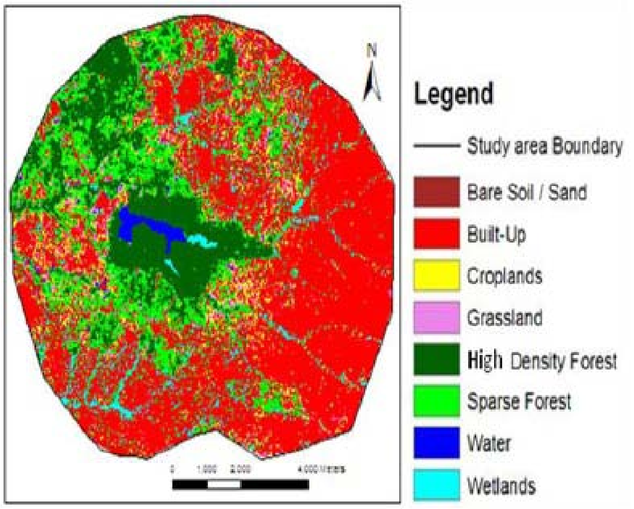

Fig.7: 2007 classified map of Owabi catchment

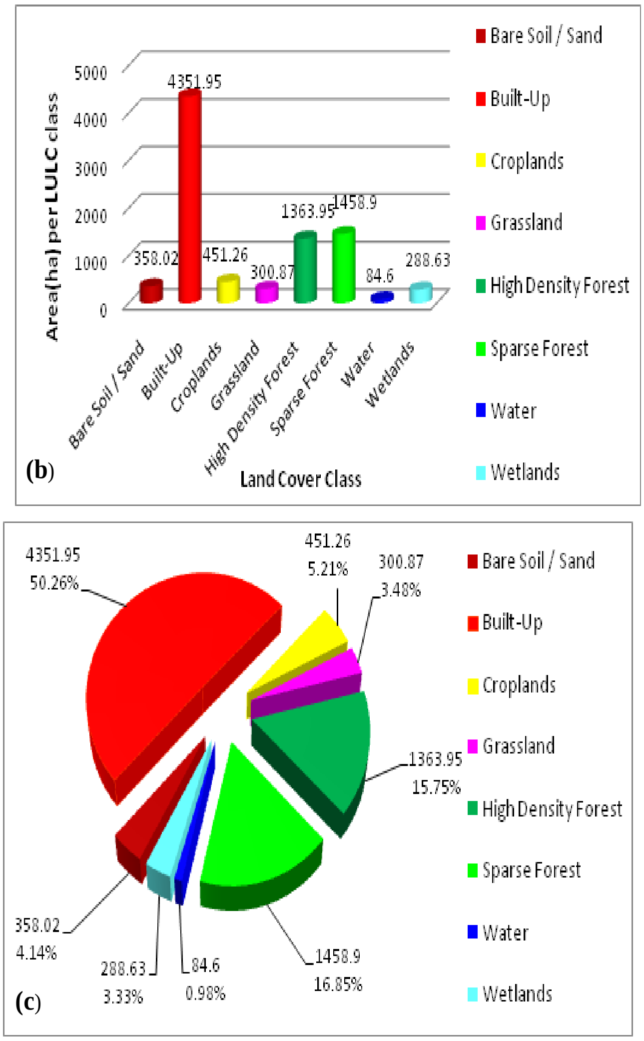

FIG. 8 LAND AREAS (HA) OF 2007 LULC CLASSES (A) AND THEIR PERCENTAGES (B)

In 1986 LULC map High Density Forest (HDF) occupies the highest percentage of area having 50.21% while Sparse Forest (SF) covers 21.29% however built-up and croplands occupies 13.01% and 1.73% respectively (Figures 3 and 4) but in the 2002 LULC map, HDF and SF reduced to 27.60% and 19.23% respectively, while built-up and croplands increased to 39.06% and 3% respectively (Figures 5 and 6). In 2007, there was a further reduction of HDF and SF to 15.75% and 16.85% respectively while built-up further increase to 50.26% which is the highest area coverage, and croplands also increased further to 5.21% (Figure 7 and 8). Generally, it is noted that the land areas of HDS and SP have decreased with increase of land areas for build up and croplands. Factors, which could influence this trend, are the population expansion, rapid urbanization, sand winning activities, and uncontrolled grazing (specially the low canopy forest areas) but these are not investigated. Further analysis of these factors is needed to better explain the impact of these factors on forest cover change.

Accuracy Assessment of LULC Classes

As previously mentioned, accuracy assessment of the classified image is an important step in image classification. The quality of a thematic map from a satellite image is determined by its accuracy. A classification accuracy assessment was performed on the 2007 Landsat ETM image and an assessment report was obtained having an error matrix, accuracy totals and a kappa statistics (as in Table 1). An overall classification accuracy of 79.53% and a Kappa coefficient (overall kappa statistics) of 0.7465 was achieved. Only wetland has producer's accuracy of 44.44%. Water and grassland have producer's accuracy of 50% each with bare soil having the highest, 92.31%. All the remaining LULC classes were having their accuracies above 50%.

TABLE 1 SUMMARY OF ACCURACY (%) AND KAPPA STATISTICS

LULC	Producers Accuracy	Users Accuracy
Water	50.00	75.00
Bare Soil / Sand	92.31	75.00
Grassland	50.00	85.71
Built-Up	92.11	85.37
parse Forest	80.56	70.73
High Density Forest	88.89	85.11
Croplands	58.33	77.78
Wetlands	44.44	66.67
Overall Classification Accuracy =79.53%		
Overall Kappa Statistics = 0.7465		

The user's accuracies of all the LULC types were above 60% with grassland having the highest accuracy of

85.71%.Accuracy assessment were not performed on the 1986 TM and the 2002 ASTER images due to unavailability of ground validation data and reference points. This has being one of the major problems of remote sensing [20]. To determine the accuracy of classification for these images, stratified random sampling method [20] could be used to generate reference points for the whole of the study area.

LULC Change Trend from 1986 to 2007

The trend analysis of the Owabi catchment reveals a change in size of the eight LULC over the 21 year period of the study (Table 2). Built-up experienced the most positive change while high density forest experienced the most negative change. The results also indicate that from 1986 to 2002, built-up, croplands and grassland experienced a positive change in area while bare soil/sand, high density forest, sparse forest, water and wetland experienced a negative change. From 2002 to 2007, bare soil/soil, built-up, croplands and water have their areas experiencing a positive change, while that of grassland, high density forest, sparse forest and wetland experienced a negative change.

TABLE 2 LULC CHANGE TREND FROM 1986 TO 2007

	Change (ha)		% Change	
LULC	**1986-2002**	**2002-2007**	**1986-2002**	**2002-2007**
Bare Soil/ Sand	-109.98	197.64	-1.27	2.29
Built-Up	2255.13	970.02	26.05	11.2
Croplands	110.07	191.43	1.27	2.21
Grassland	36.00	-112.59	0.41	-1.29
High Density Forest	-1957.95	-1025.37	-22.61	-11.85
Sparse Forest	-178.65	-206.19	-2.07	-2.38
Water	-72.81	24.21	-0.84	0.28
Wetlands	-81.81	-39.15	-0.94	-0.46

LULC Conversion Analysis within the Owabi Catchment

The summary of the major LULC conversions that have been taken place from 1986 to 2007 within the Owabi catchment is in Table 3. The diagonal of this Table shows the LULC proportions that remain unchanged from 1986 to 2007a total area of 2,457.72 ha representing 28.4% of the study area.

TABLE 3 LULC CONVERSIONS FROM 1986 TO 2007

LULC	Water	Bare Soil/ Sand	Grass Land	Built-Up	Sparse Forest	High Den. Forest	Crop Lands	Wet Lands	Total Area (ha)
Bare Soil/ Sand	31.68	3.33	3.42	50.04	11.97	19.53	5.13	8.10	13.20
Built-Up	0.45	15.03	10.71	164.61	41.22	13.95	16.47	8.46	270.36
Crop lands	0.63	20.43	14.76	223.83	64.71	18.72	23.67	10.71	377.46
Grass land	0.63	37.17	25.92	968.76	36.36	4.86	36.54	16.56	1126.80
High Den. Forest	5.49	94.77	68.76	1045.71	294.93	155.52	109.53	69.03	1843.74
Sparse Forest	25.83	156.78	158.85	1606.05	939.51	1090.26	232.02	137.97	4347.27
Water	0.36	9.36	4.95	101.88	17.37	3.6	8.37	3.87	149.76
Wet lands	19.53	21.15	14.04	191.07	52.83	57.51	19.53	33.93	409.59
Total Area (Ha)	84.6	358.02	300.87	4351.95	1458.90	1363.95	451.26	288.63	8658.18

What is the most evident in the results is that, high density forest made the highest conversion of 1606.05 ha to built-up representing 18.6% of the area. Similarly, 1045.71 ha of sparse forest were converted to built-up, representing 12.08%. The conversion of high density forest to other LULC classes such as water, bare soil, grassland, croplands and wetlands are 25.83ha (0.3%), 156.78ha (1.8%), 158.85ha (1.84%), 232.02ha (2.68%) and 137.97ha (1.6%) respectively. Other LULC conversions are grassland to croplands 23.67 ha, wetlands to built-up 191.07 ha, croplands to sparse forest 17.37 ha, sparse forest to croplands 109.53 ha.

Normalized Difference Vegetation Index

Using equations 1 and 2 in Section II.E NDVI images (Figure 9) of the study area were generated from the 1986 Landsat TM (Figure 9a), 2007 Landsat ETM (Figure 9c) and 2002 ASTER imagery (Figure 9b). The digital numbers (DN's) of the pixels for the resultant map ranged from 0 to 255. Applying Groten and Ocatre [17] rule (as in Section II.E), pixels with DN greater than 135 appear red in colour which could either is a forest or a cultivated land. DN values less

than 135 indicate water bodies, bare soil, and built-up area or degraded grassland. Forest areas turn to have higher NDVI values due to their greater green biomass.

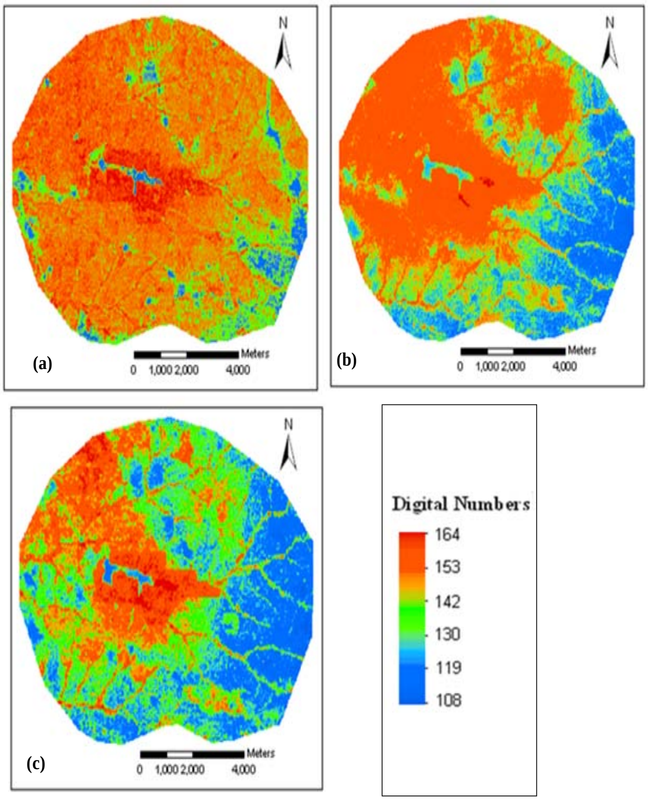

FIG.9 NDVI AGGREGATE MAP SHOWING FOREST COVERS AND OTHER LULC TYPES

The NDVI gave very good results in identifying forest areas for subsequent investigation and data collection during fieldwork. Although, it was not tested statistically, but there seems to be no significant difference between the results obtained from NDVI classification and those obtained from the supervised classification.

Spatial Distribution of the Reserved Forest

The 1974 topographic with the boundary and distribution of the forest reserve (as shown in Figure 1b)was digitized and re-projected in GIS environment. Towns and settlements were subsequently added by clipping with the study area boundary. The total area of the reserved forest was obtained and its value was noted as 1,315.58m^2. The digital boundary map was overlaid into the generated LULC maps in Figures 3, 5 and 7 so as to obtain a visual representation of the extend of changes that occurred in 1986, 2002 and 2997.The results of this overlay operations are shown in Figures 10a (1986 LULC map), 10b (2002 LULC map), and 10c (2007 LULC map).As can be seen visually in Figure 10c, the reserved forests have been highly depleted over the period, from 1974 to 2007.This remarkable change in vegetation has been the results of anthropogenic activities in the study area.

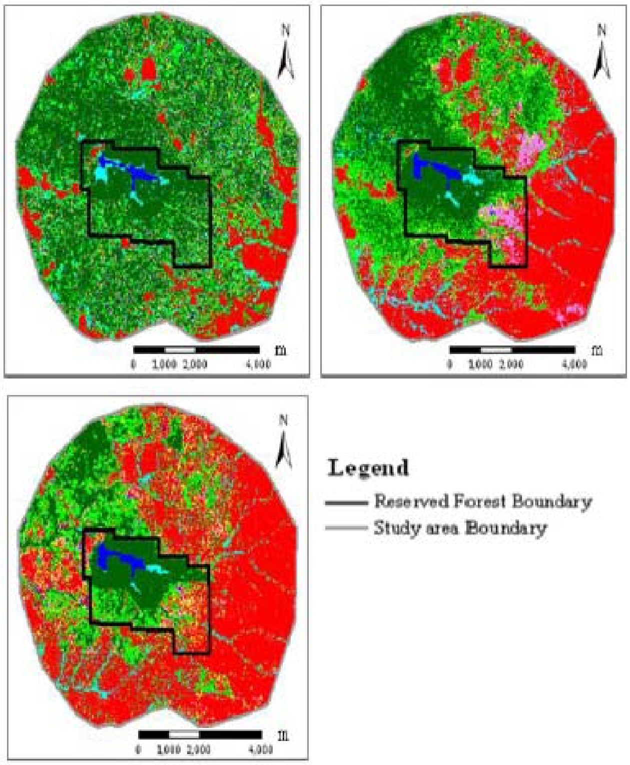

FIG. 10 OVERLAY OF 1974 MAP AND LULC MAPS OF 1986, 2002 AND 2007

Conclusions and Recommendations

The relationship between the forest covers and its associated LULC classes were investigated and various thematic maps were developed. The main LULC types identified in the catchment are bare soil/sand, built-up, croplands, grassland, high density forest, sparse forest, water and wetlands. It was observed that vegetation has changed remarkably from the period 1986-2007. This decrease in vegetation has been as a result of anthropogenic activities in the study area but these were not investigated. Therefore further analysis of these factors is needed to better explain the impact of these factors on forest cover change

Also, by taken more factors such as rainfall, soil moisture etc. into consideration, the study could reach a higher accuracy for forest cover change detection. Performing multi sensor data classification using neural networks by combination of ancillary data (i.e. elevation and aspect) with the Landsat image data would improve the classification result and produce higher accuracy than the use of Landsat image data only. When

multi-temporal satellite data and multiyear ground truth data are available, it may be possible and useful to do further studies about change detection analysis to detect deforestation, built-up expansion and other LULC changes within the catchment. Future studies are recommended to assess the prediction of forest cover, which are under risk of invasion.

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